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A Lightweight Deep Learning Model for The Early Detection of Epilepsy

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Abstract-Epilepsy is a neurological disorder and non communicable disease which affects patient's health, During this seizure occurrence normal brain function activity will be interrupted. It may happen anywhere and anytime so it leads to very dangerous problems like sudden unexpected death. Worldwide seizure affected people are around 65% million. So it must be considered as serious problem for the early prediction. A number of different types of screening tests will be conducted to assess the severity of the symptoms such as EEG,MRI, ECG, and ECG. There are several reasons why EEG signals are used, including their affordability, portability, and ability to display. The proposed model used bench-marked CHB-MIT EEG datasets for the implementation of early prediction of epilepsy ensures its seriousness and leads to perfect diagnosis. Researchers proposed Various ML /DL methods to try for the early prediction of epilepsy but still it has some challenges in terms of efficiency and precision Seizure detection techniques typically employ the use of convolutional neural networks (CNN) and a bidirectional short- and long-term memory (Bi-LSTM) model in the realm of deep learning. This method leverages the strengths of both models to effectively analyze electroencephalogram (EEG) data and detect seizure patterns. These light weight models have been found to be effective in automatically detecting seizures in deep learning techniques with an accuracy rate of up to 96.87%. Hence, this system has the potential to be utilized for categorizing other types of physiological signals too, but additional research is required to confirm this.

Keywords: Deep Learning, EEG, CNN, Bi-LSTM, Epileptic Seizure.

1. INTRODUCTION

Seizures, which are abrupt bursts of electrical activity in the brain, are a recurring and unexpected feature of the neurological condition epilepsy. Effective management and treatment of epilepsy depend on the accurate and prompt detection of seizures. Traditional seizure detection techniques frequently rely on skilled professionals manually reviewing electroencephalogram (EEG) data, It can take time and is prone to error.CNNs and Bi-LSTM have developed into useful technologies. for automated seizure diagnosis thanks to developments in deep learning techniques. Bi-LSTM networks are efficient at modelling temporal dynamics and collecting long-range dependencies in the data, whereas CNNs are excellent at catching spatial dependencies and extracting significant features from raw EEG data.

CNNs are particularly well-suited for analyzing the spatial patterns and local features present in the EEG signals.Through the application of a collection of teachable filters to the supplied data, they conduct feature extraction using convolutional layers. The filters scan the data, capturing patterns such as frequency oscillations, transient spikes, or waveform shapes that are indicative of seizures. By further downsampling the retrieved features, pooling layers can reduce computational complexity and improve the generalizability of the network.Bi-LSTM networks, on the other hand, are intended to simulate the temporal dynamics of the EEG data. With their recurrent connections and memory cells, LSTM (Long Short-Term Memory) units may identify temporal patterns in the input and capture long-range dependencies.Researchers have created hybrid architectures that make use of the advantages of both CNNs and Bi-LSTM networks. The Bi-LSTM layers model the temporal relationships and capture the long-term dependencies in the EEG signals using the spatial information that the CNN layers have extracted from the raw EEG data. In fully connected layers for classification, where the final seizure occurrence prediction is formed,the Bi-LSTM layers' output is fed.The combination of CNNs and Bi-LSTM networks has produced promising results in the automatic and accurate seizure identification from raw EEG data.

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The hybrid model's ability to capture spatial and temporal information simultaneously can lead to improved performance in seizure detection tasks. The combination of CNN and BiLSTM helps the model learn complex representations and capture important features related to seizures, resulting in more accurate predictions.The effectiveness and dependability of epilepsy diagnosis and monitoring might be greatly increased with the help of these deep learning models, which would ultimately result in better patient management and therapy.The hybrid model can offer some level of interpretability by allowing analysis of the learned features from both the CNN and BiLSTM components. The CNN can highlight important spatial patterns in the EEG signals, while the BiLSTM can provide insights into the temporal dynamics associated with seizures.Fig. 1. shows that the proposed Frame Work of Hybrid Light Weight Model.Previous studies have proposed a number of detection algorithms. EEG signals are used for feature extraction. EEG signal we can get from frequency-domain, time-domain time-frequency analysis, wavelet analysis, and more. After features are extracted, the classification phase often uses machine learning classifiers or other algorithms. Valid methodology for epileptic seizures detecting with EEG using machine learning algorithm

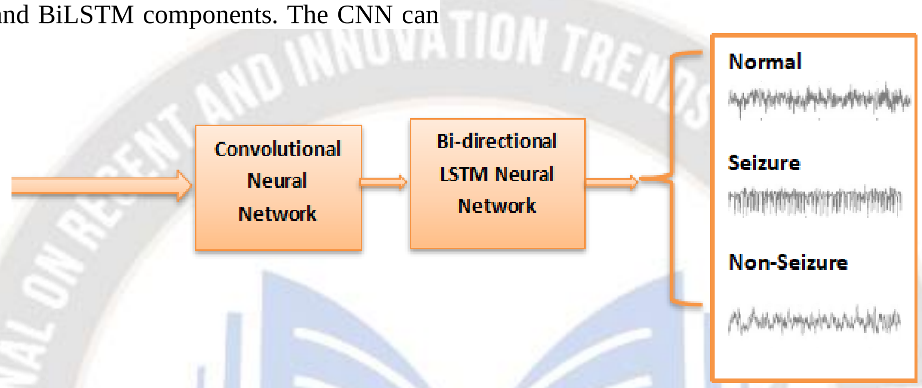

Fig. 1. Frame Work of Proposed Hybrid Light Weight Model

Electroencephalography (EEG) monitors the activity of brain for epilepsy patients. It takes a lot of time to read EEG data clinically even hundreds of hours. As a result, seizure detection that is automatic is crucial. The assessment and diagnosis of epileptic seizures is being developed using automated techniques that use electroencephalography signal.

2. RELATED WORKS

A hybrid model that merged CNN and Bi-LSTM layers was proposed by Islam et al.[1]for seizure detection in EEG signals.extracted spatial features from the spectrograms of EEG signals, and the Bi-LSTM component captured temporal dependencies.model achieved high accuracy in detecting seizures on the CHB-MIT dataset, outperforming other traditional machine learning approaches.Zhang et al.[2]results showed that the hybrid models combining CNN and Bi-LSTM achieved superior performance compared to individual models. Acharya et al.[3]The proposed hybrid models achieved high accuracy in detecting seizures on the Bonn University EEG dataset.To extract spatial characteristics from individual EEG channels, CNN models were used., and Bi-LSTM models were employed to capture temporal dependencies across multiple channels.Khan et al.[4]The models were evaluated on the Bonn University EEG dataset, and the outcomes demonstrated that hybrid models combining CNN and Bi-LSTM achieved superior accuracy compared to individual models.

3. METHODOLOGY

Deep Learning Model(DL)

Deep learning (DL) has demonstrated near-human skills to handle various tasks in recent years, and has been particularly successful in picture classification, object recognition, and segmentation[7]. The accuracy of the classification is heavily influenced by feature extraction, which is a crucial phase in the process. In this process, the crucial phase is feature extraction. The accuracy of the classification is heavily influenced with the current advancement of deep learning (DL), we audaciously anticipate a method in which categorization is carried out without the need for intricate feature extraction.Convolutional neural network designs (CNNs) and recurrent neural networks (RNNs), especially long short-term memory (LSTM) and gated recurrent unit (GRU) variations, are common designs utilised in seizure prediction.For seizure detection, an appropriate deep learning neural network structure is used. Recurrent neural networks (RNNs), such as long short-term memory (LSTM) networks or gated recurrent units (GRUs), and convolutional neural networks (CNNs) are popular options. These structures were created to, respectively, capture spatial or temporal patterns in the EEG data.

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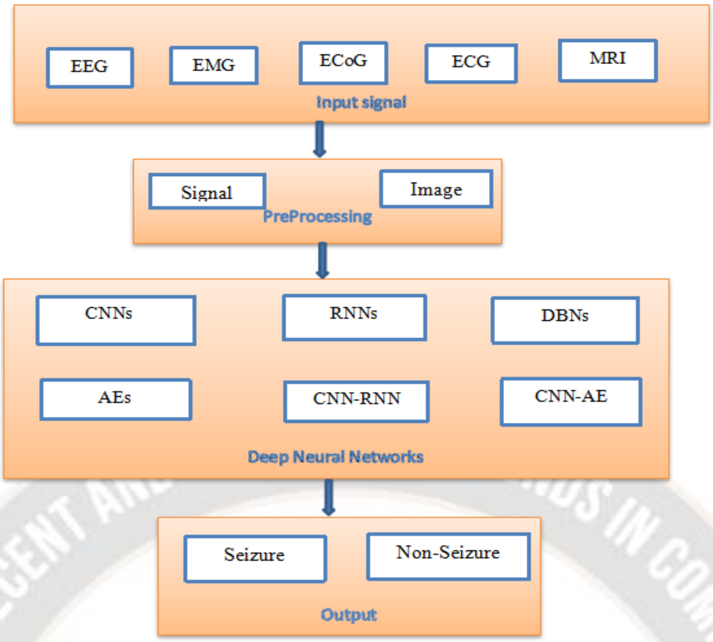

Fig.2. Block Diagram of Deep Learning Based System

DL automatically extracts the features of global synchronization, Without any prior knowledge,. It appears that feature extraction before classification is better than feeding the classifier with raw EEG data[8].The raw EEG data was used to train the Deep Learning models. Nowadays, feature extraction is not done.. A predictive analytic model works on healthcare to learn from patient past history (data) to forecast upcoming illness and to choose the appropriate course of therapy.Fig.2, demonstrates the genral outline and numerous uses of deep learning models including Recurrent Neural Network, LSTM/Bi-LSTM, CNN), GRU, and RBM the discipline of healthcare are discussed. The findings indicate that the Bi-LSTM/LSTM model is frequently used for medical data in time-series and CNN is frequently used for medical picture data.A deep learning model can help medical practitioners make judgement about prescriptions and hospitalizations rapidly, saving time and benefiting the healthcare sector. This study examines the a variety of deep learning prediction models are healthcare application

Datasets Description

The data used for the analysis was gathered from the CHB-MIT dataset, which is a collaboration between Children's Hospital Boston and the Massachusetts Institute of Technology. There are a total of 5 folders, each containing 100 files that are unique. Each of the 23 chunks that make up the data points has 178 data points in it. Every data point shows the recorded EEG value at a distinct time point.The 178-dimensional input vector's category is represented by the final column, "y," which accepts values between 1 and 5. A value of,5 in particular signifies that the patient's eyes opened when an EEG signal was being used to capture their brain activity. 4 - The patient's eyes closed while the EEG signal was being used to measure brain activity.3 -Recorded the EEG activity from the tumor-affected part of the brain and identified the healthy brain area. 2-They recorder tumor located area from the EEG signal.1Seizure Activity is recorded.

Table.1.CHB-MIT Dataset

Dataset	Subjects	Duration	output
CHB-MIT	500 (Male & Female)	23.5 seconds	Seizure/Non- Seizure

Convolutional Neural Network

The goal for working out a CNN aims to change the network's weights. to lessen the loss function and improve prediction accuracy. The weights' updating method is performed through backpropagation and optimization algorithms[12] To clarify,

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the activations inThe result of providing input is the output layer. data forward through the network using the learned weights. The output layer applies the final transformation to the input features and produces the predictions or scores for the different classes in a classification problem. The activations in the output layer are not updated during the training process; they are determined using the network's most recent weights.. The actual updating of the weights in a CNN is performed through backpropagation, which involves calculating the gradients weights in the opposite direction as the gradients in an effort to reduce the loss.This process iteratively updates the weights throughout the system, including the fully connected layers, convolutional layers and any other trainable layers.

Fig.3 demonstrates a fully linked deep neural network's topology.The three layers that make up a deep neural network are the input layer, hidden layer, and output layer. iterative layer comes first, the output layer comes last, and the concealed layer comes in the middle. In the deep learning training method, the deep neural network's structure is first initialised in accordance with the requirements, the layer is then transferred across layers to obtain an error, and finally back propagation is carried out. Use of the stochastic gradient descent method calculate each parameter, choose the direction of descent, and update each parameter in accordance with the principle of error minimization. DNNs come in a variety of forms and have been used in Because the data sets are typically distinct, it is difficult to evaluate the performance of various DNNs, despite the fact that they have many variations and have been successfully used in other domains.

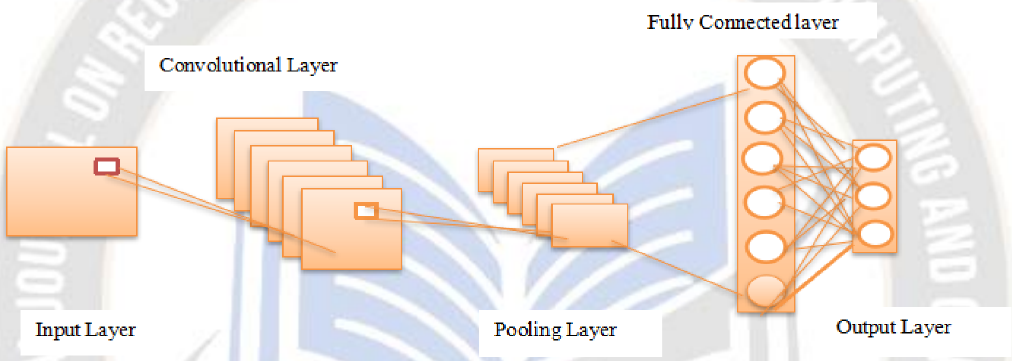

Fig. 3. Convolutional Neural Network

Input Layer:

he EEG signals, which are commonly recorded as multi-channel time-series data, are accepted as input by the input layer.EEG signals can be visualised as a 2D spectrogram or as a 1D signal with several channels.

Convolutional Layers:

Seizure prediction CNNs have convolutional layers that allow the network to automatically extract pertinent characteristics from the input EEG data, efficiently capturing spatial patterns and enhancing the model's seizure detection capabilities.y (i,j) in this case refers to the output at coordinates (i,j) on the feature map.The input data at location (i-m,j-n) is x [i-m,j-n]. The learnable weights of the convolutional filter at location (m,n) are represented by w[m,n]. The biassed word is b.

$$y(i,j) = m\ Nx(i,j).w[m,n]+b$$

By moving the convolutional filter across the input data, the convolution operation is carried out. The dot product between each position's associated input values (x) and the filter weights (w) inside the receptive field is calculated. To get the output value (y) at that place, the resulting dot products are added together, and the bias factor (b) is subtracted.

Activation Function

ReLU is widely used in CNNs due to its simplicity and effectiveness in capturing non-linearities. The ReLU function computes the output as the maximum between 0 and the input value.

ReLU(x) = max(0, x)

FC Layers:

Fully connected layer function is represented by the equation y=f(Wx+b), in which is the final result vector of the FC layer.In the FC layer of the linear transformation, the input vector is defined by the weight matrix, which has the activation function F() applied element-by-element.B is the bias vector.

Output Layer:

The sigmoid function goal is to classify between seizure and non-seizure instances.It maps the input to a range between 0 and 1, representing the probability of belonging to the positive

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class (seizure). Sigmoid(x) is equal to 1 / (1 + exp(-x)) The input to the sigmoid function is represented by x.

Bi-LSTM Model

The pre processed EEG data, which is commonly represented as a series of fixed-length time windows or segments, is sent into the model as input. One or more Bi-LSTM layers receiveinput of the input sequence. Forward and backward LSTM units make up each Bi-LSTM layer,which handles both the forward and backward orientations of the input sequence. The network can detect temporal relationships and long-range patterns in the EEG data thanks to its bidirectional processing[18]. After the Bi-LSTM layers, dropout layers may be added to prevent overftting. Dropout assists in regularization and enhances generalization by setting only some of the input units to 0 at random throughout training

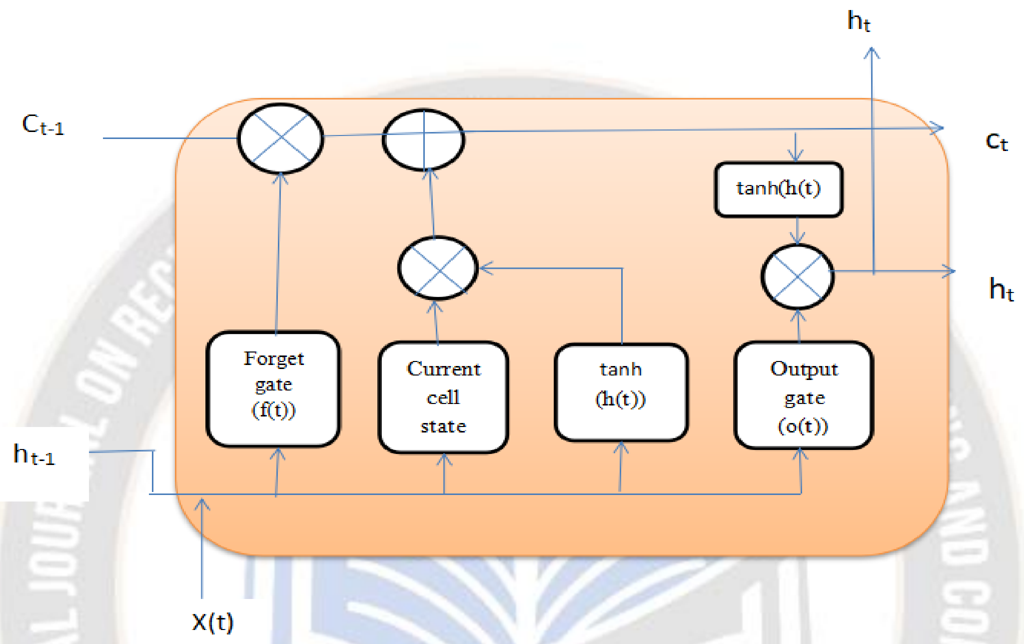

Fig.4 Bidirectional LSTM

Figure 4 illustrates how the Long Short-Term Memory (LSTM) architecture of recurrent neural networks (RNNs) was developed to solve the vanishing gradient problem and identify long-term dependencies in sequential data. It is quite good at representing temporal correlations and has been widely used in a number of tasks, including speech recognition, machine translation, and time series analysis. detecting seizures is included.The memory cells and gates that control the information flow in the network make up the fundamental LSTM architecture. The cell state, which is an internal state that is maintained by each LSTM unit and acts as a memory to store and propagate information over time. The BiLSTM model architecture is suitable for seizure detection because it can recognise persistent dependence and temporal dynamics in EEG signals.The BiLSTM model could gather contex .By processing the input sequence both forward and backward, the BiLSTM model may gather context from both the past and the future. the model's comprehension of the temporal relationships between the data at smaller time increments. By introducing strategies like dropout regularisation or attention mechanisms to boost generalisation and focus on pertinent characteristics, the structure can be further improved.The key components of an LSTM unit are:

Cell State (C_t):

The LSTM's memory is its cell state unit and allows data to flow through network over long sequences.It acts as a conveyor belt, selectively retaining and passing important information while allowing irrelevant information to be ignored.The cell state is updated then modified through gates.

Input Gate (i_t):

The amount of additional information from the current input should be added to the cell state is selected by the input gate.It applies a sigmoid activation function on input characteristics, typically the input for the current time step and the prior hidden state, to yield values between 0 and 1.The input gate controls how fresh data enters the cell state.

Forget Gate (f_t):

The forget gate controls how much information about the previous cell state should be kept or thrown away.It uses a sigmoid activation function on input characteristics and the

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prior concealed state.The forget gate outputs values in the range of 0 and 1, indicating how much each cell state component should be forgotten.

Output Gate (o_t):

The gate that outputs the result chooses how much of the hidden state should be produced from the present cell state.The sigmoid activation function is used to activate the input features and the prior hidden state, then passes the output by compressing the values between -1 and 1 using a tanh activation function.The information that moves from the cell state to The output gate has control over the concealed state.Progressive Propagation: The prior hidden state at time step t-1, the prior hidden state at time step t, and the prior cell state at time step t-1 are all examples of past states. At time step t, the forward LSTM layer receives the following inputs: x(t), h(t-1) (initialised as 0 at the start), the prior hidden state, and c(t-1).These are the computations that make up an LSTM unit.

- Calculate the input gate (i_t) using input features and the previous hidden state.
- Calculate the forget gate (f_t) using input features and the previous hidden state.
- Calculate the output gate (o_t) using input features and the previous hidden state.
- Calculate a candidate cell state (C~_t) by applying the tanh activation function to a combination of input features and the previous hidden state.
- Update the current cell state (C_t) by combining the forget gate, the input gate, and the candidate cell state.
- Calculate the hidden state (h_t) by applying the output gate to the current cell state

The network has the ability to selectively recall or forget information depending on the input and the previous state thanks to the LSTM architecture. This makes it possible for the model to successfully capture long-term interdependence and handle sequential data. Deeper LSTM layers can be created by combining many LSTM units, which enables the model to learn hierarchical representations and recognise more intricate patterns in the input.BPTT, or back-propagation through time, which applies The LSTM network is trained using the backpropagation technique for recurrent neural networks. The model can learn from sequential input and produce precise predictions since the gradients are computed over time and utilised to update the weights of the LSTM units.After the Bi-LSTM layers, one or more fully connected layers can be added. These layers further process the representations that were learned in the Bi-LSTM levels. After each fully linked layer,ReLU and other non-linear activation functions are widely used to introduce non-linearity.The output layer, which offers the seizure prediction, is coupled to the last fully integrated layer. a single neuron for binary classification with sigmoid activity (seizure vs. no-seizure) or multiple neurons with a multi-class classification softmax activation function (if there are various types of seizures to be classified) may be present Depending on the specific task in the output layer. The model parameters (weights and biases) are learned throughout the training phase by optimising an appropriate loss function, Cross-entropies, such as binary or categorical cross-entropies, can be computed using techniques such as backpropagation and gradient descent. EEG data that has been labelled to indicate whether seizures were present or absent is used to train the model.

Hybrid model of CNN and Bi-LSTM

Convolutional neural networks (CNN) and bidirectional long short-term memories (BiLSTM) are combined. model can be an effective approach for seizure detection. This type of model can capture both spatial and temporal information present in Electroencephalography (EEG) signals, which are commonly used for seizure detection. By combining the strengths of CNNs in capturing spatial features and BiLSTMs in capturing temporal dependencies, the hybrid CNN-BiLSTM model can effectively learn representations from EEG signals for seizure detection. The accuracy of the models in Figures 6 and 7 is 91% and 96%, respectively, for models based on Bi-LSTM and CNN, respectively.

4. RESULT ANALYSIS OF CNN AND BI-LSTM

The Light weight models of CNNs and Bi-LSTM networks in epilepsy seizure detection has shown promising results, providing automated and accurate detection of seizures from raw EEG data. The effectiveness and dependability of epilepsy diagnosis and monitoring could be greatly increased by these deep learning models, which would ultimately result in better patient management and epileptic treatment.

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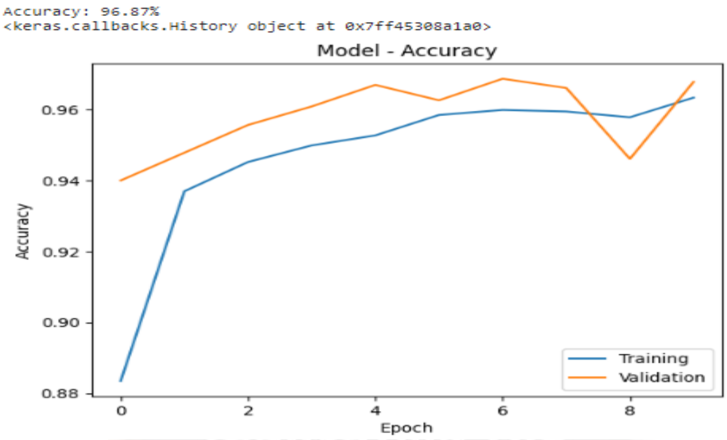

Fig.6. Plot of CNN Model Accuracy

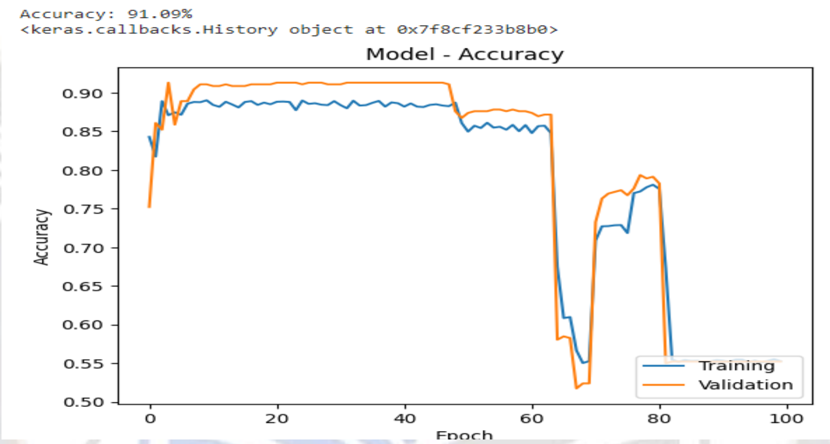

Fig.7. Plot of Bi-LSTM Model Accuracy

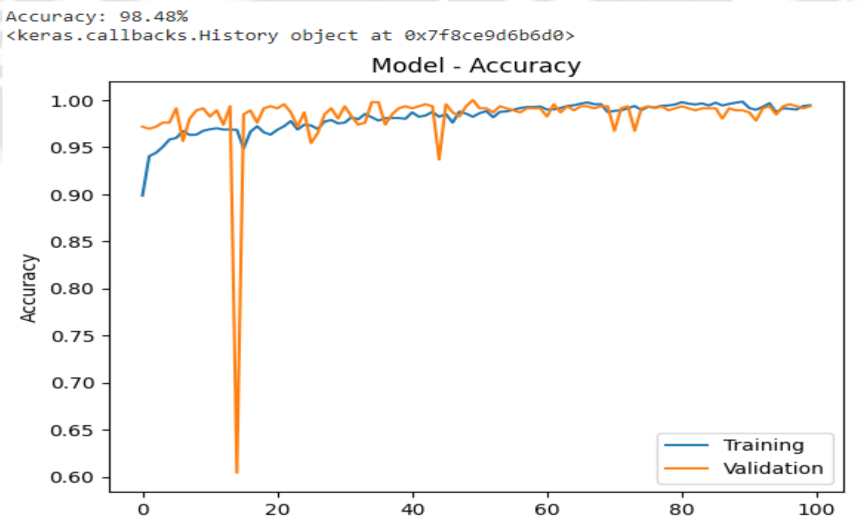

Fig.8 Plot of Hybrid Light Weight Model Accuracy

5. CONCLUSION

The proposed A light weight deep learning automated model for detecting epilepsy has been developed. The models use deep learning and can classify between two types (epileptic and interictal: epileptic and non-epileptic) or three types (interictal, non-epileptic, epileptic). The EEG signals may be effectively processed by CNN's to extract spatial features that can be used to identify seizure patterns. Bi-LSTMs can detect long-range patterns and temporal dependencies in the EEG data, which improves comprehension of seizure dynamics

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CONFLICT-OF-INTEREST STATEMENT

The authors have no conflicts of interest to declare.All co-authors have seen and agree with the contents of the manuscript. We certify that the submission is original work and is not under review at any other publication.

FUNDING INFORMATION

The authors we declare that we have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

[1.] Beeraka, S.M., Kumar, A., Sameer, M. et al. Accuracy Enhancement of Epileptic Seizure Detection: A Deep Learning Approach with Hardware Realization of STFT. Circuits Syst Signal Process 41, 461–484 (2022). https://doi.org/10.1007/s00034-021-01789-4

[2.] Singh, K., Malhotra, J. Two-layer LSTM network-based prediction of epileptic seizures using EEG spectral features. Complex Intell. Syst. 8, 2405–2418 (2022)./doi.org/10.1007/s40747-021-00627-z

[3.] Adeli, S. Ghosh-Dastidar and N. Dadmehr, "A Wavelet-Chaos Methodology for Analysis of EEGs and EEG Subbands to Detect Seizure and Epilepsy," in IEEE Transactions on Biomedical Engineering, vol. 54, no. 2, pp. 205-211, Feb. 2007, doi: 10.1109/TBME.2006.886855.

[4.] Chandler, J. Bisasky, J.L.V.M. Stanislaus, T. Mohsenin, Real-time multi-channel seizure detection and analysis hardware, in IEEE Biomedical Circuits and Systems Conference (BioCAS), San Diego, CA, USA (2011), pp. 41–44. https://doi.org/10.1109/BioCAS.2011.6107722

[5.] Acharya et al. "Seizure Detection Using Deep Learning Models With Multi-Channel EEG Signals" 2018 International Conference on Electronics, Information, and Communication (ICEIC), Honolulu, HI, USA, 2018, pp. 1-5, doi: 10.23919/ELINFOCOM.2018.8330671.

[6.] Wei, X., Zhou, L., Chen, Z. et al. Automatic seizure detection using three-dimensional CNN based on multi-channel EEG. BMC Med Inform Decis Mak 18 (Suppl 5), 111 (2018). https://doi.org/10.1186/s12911-018-0693-8

[7.] Y. Yuan et al., "A novel channel-aware attention framework for multi-channel EEG seizure detection via multi-view deep learning," 2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI), Las Vegas, NV, USA, 2018, pp. 206-209, doi: 10.1109/BHI.2018.8333405.

[8.] Cheng, S. He, V. Stojanovic, X. Luan, F. Liu, Fuzzy fault detection for Markov jump systems with partly accessible hidden information: an event-triggered approach. IEEE Trans. Cybern. (2021). https://doi.org/10.1109/TCYB.2021.3050209 .

[9.] McSharry, P., Smith, L. & Tarassenko, L. Prediction of epileptic seizures: are nonlinear methods relevant?. Nat Med 9, 241–242 (2003). https://doi.org/10.1038/nm0303-241

[10.] Tao, J. Li, Y. Chen, V. Stojanovic, H. Yang, Robust point-to-point iterative learning control with trial-varying initial conditions. IET Control Theory Appl. 14(19), 3344–3350 (2020). https://doi.org/10.1049/iet-cta.2020.0557

[11.] Sokolova, M., and Lapalme, G. (2009). A systematic analysis of performance measures for classification tasks. Inform. Process. Manag. 45, 427–437. doi: 10.1016/j.ipm.2009.03.002

[12.] Wang, D., Ren, D., Li, K., Feng, Y., Ma, D., Yan, X., et al. (2018). Epileptic seizure detection in long-term EEG recordings by using wavelet-based directed transfer function. IEEE Transact. Biomed. Eng. 65, 2591–2599. doi: 10.1109/tbme.2018.2809798

[13.] Wang, X., Zhao, Y., and Pourpanah, F. (2020). Recent advances in deep learning. Int. J. Mach. Learn. Cybern. 11, 747–750. doi: 10.1007/s13042-020-01096-5

[14.] Wei, X., Zhou, L., Zhang, Z., Chen, Z., and Zhou, Y. (2019). Early prediction of epileptic seizures using a long-term recurrent convolutional network. J. Neurosci. Methods 327:108395. doi: 10.1016/j.jneumeth.2019.108395

[15.] Yavuz, E., Kasapbaşı, M. C., Eyüpoğlu, C., and Yazıcı, R. (2018). An epileptic seizure detection system based on cepstral analysis and generalized regression neural network. Biocybern. Biomed. Eng. 38, 201–216. doi: 10.1016/j.bbe.2018.01.002

[16.] 12.Gramacki, A., Gramacki, J. A deep learning framework for epileptic seizure detection based on neonatal EEG signals. Sci Rep 12, 13010 (2022). https://doi.org/10.1038/s41598-022-15830-2.

[17.] Yuan, Y., Xun, G., Jia, K., and Zhang, A. (2017). "A multi-view deep learning method for epileptic seizure detection using short-time fourier transform," in Proceedings of the 8th ACM International Conference on Bioinformatics, Computational Biology, and Health Informatics, New York, NY. doi: 10.1145/3107411.3107419

[18.] Zhou, M., Tian, C., Cao, R., Wang, B., Niu, Y., Hu, T., et al. (2018). Epileptic Seizure detection based on EEG signals and CNN. Fronti. Neuroinform. 12:95. doi: 10.3389/fninf.2018.00095

[19.] Ma et al., "A Multi-Channel Feature Fusion CNN-Bi-LSTM Epilepsy EEG Classification and Prediction Model Based on Attention Mechanism," in IEEE Access, vol. 11, pp. 62855-62864, 2023, doi: 10.1109/ACCESS.2023.3287927.

[20.] 15.A. M. Abdelhameed, H. G. Daoud and M. Bayoumi, "Deep Convolutional Bidirectional LSTM Recurrent Neural Network for Epileptic Seizure Detection," 2018 16th IEEE International

New Circuits and Systems Conference (NEWCAS), Montreal, QC, Canada, 2018, pp. 139-143, doi: 10.1109/NEWCAS.2018.8585542.

[21.] Lu, A. Wen, L. Sun, H. Wang, Y. Guo and Y. Ren, "An Epileptic Seizure Prediction Method Based on CBAM-3D CNN-LSTM Model," in IEEE Journal of Translational Engineering in Health and Medicine, vol. 11, pp. 417-423, 2023, doi: 10.1109/JTEHM.2023.3290036.

[22.] Rogowski, Z., Gath, I. & Bental, E. On the prediction of epileptic seizures. Biol. Cybern. 42, 9–15 (1981). https://doi.org/10.1007/BF00335153

[23.] Salant, Y., Gath, I. & Henriksen, O. Prediction of epileptic seizures from two-channel EEG. Med. Biol. Eng. Comput. 36, 549–556 (1998). https://doi.org/10.1007/BF02524422

[24.] Raghu, S., Sriraam, N., Vasudeva Rao, S. et al. Automated detection of epileptic seizures using successive decomposition index and support vector machine classifier in long-term EEG. Neural Comput & Applic 32, 8965–8984 (2020). https://doi.org/10.1007/s00521-019-04389-1

[25.] Yuan and D. Wei, "A seizure prediction method based on efficient features and BLDA," 2015 IEEE International Conference on Digital Signal Processing (DSP), Singapore, 2015, pp. 177-181, doi: 10.1109/ICDSP.2015.7251854.

[26.] Zhang, S., Chen, D., Ranjan, R. et al. A lightweight solution to epileptic seizure prediction based on EEG synchronization measurement. J Supercomput 77, 3914–3932 (2021). https://doi.org/10.1007/s11227-020-03426-4

[27.] R. Ozcan and S. Erturk, "Seizure Prediction in Scalp EEG Using 3D Convolutional Neural Networks With an Image-Based Approach," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 27, no. 11, pp. 2284-2293, Nov. 2019, doi: 10.1109/TNSRE.2019.2943707.

[28.] M. Abdelhameed and M. Bayoumi, "Semi-Supervised Deep Learning System for Epileptic Seizures Onset Prediction," 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA), Orlando, FL, USA, 2018, pp. 1186-1191, doi: 10.1109/ICMLA.2018.00191.

[29.] Shahbazi and H. Aghajan, "A GENERALIZABLE MODEL FOR SEIZURE PREDICTION BASED ON DEEP LEARNING USING CNN-LSTM ARCHITECTURE," 2018 IEEE Global Conference on Signal and Information Processing (GlobalSIP), Anaheim, CA, USA, 2018, pp. 469-473, doi: 10.1109/GlobalSIP.2018.8646505.

[30.] M. Varnosfaderani et al., "A Two-Layer LSTM Deep Learning Model for Epileptic Seizure Prediction," 2021 IEEE 3rd International Conference on Artificial Intelligence Circuits and Systems (AICAS), Washington DC, DC, USA, 2021, pp. 1-4, doi: 10.1109/AICAS51828.2021.9458539.

[31.] Freestone, Dean R.a,∗; Karoly, Philippa J.a,b,c,∗; Cook, Mark J.a. A forward-looking review of seizure prediction. Current Opinion in Neurology 30(2):p 167-173, April 2017. | DOI: 10.1097/WCO.0000000000000429

[32.] Liu, J. Li and M. Shu, "Epileptic Seizure Prediction Based on Region Correlation of EEG Signal," 2020 IEEE 33rd International Symposium on Computer-Based Medical Systems (CBMS), Rochester, MN, USA, 2020, pp. 120-125, doi: 10.1109/CBMS49503.2020.00030.

[33.] Wang, J. Yang and M. Sawan, "A Novel Multi-scale Dilated 3D CNN for Epileptic Seizure Prediction," 2021 IEEE 3rd International Conference on Artificial Intelligence Circuits and Systems (AICAS), Washington DC, DC, USA, 2021, pp. 1-4, doi: 10.1109/AICAS51828.2021.9458571.

[34.] Sakkos., Liu, H., Han, J. et al. End-to-end video background subtraction with 3d convolutional neural networks. Multimed Tools Appl 77, 23023–23041 (2018). https://doi.org/10.1007/s11042-017-5460-9